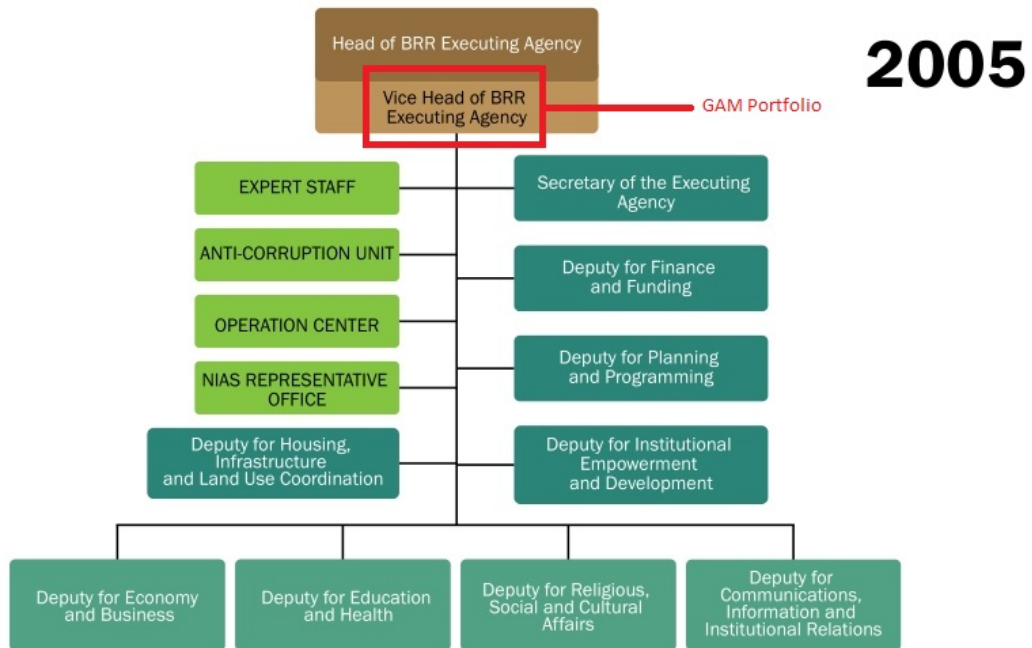


The Effect of Wartime Legacies on Electoral Mobilization after Civil War

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A Agency for the Rehabilitation and Reconstruction (BRR) Organigram



Note: Source BRR NAD-NIAS (2009, 150). Own annotation indicating GAM portfolio.

B Summary Statistics

Table 1. Summary Statistics: Sub-district level dataset

Statistic	N	Mean	Median	St. Dev.	Min	Max
Pre-Election 2006 Dummy	9,640	0.38	0	0.48	0	1
GAM support (dummy)	9,640	0.50	0	0.50	0	1
GAM support (continuous)	9,640	4.20	3.50	3.69	0.00	20.00
Aid: Number of New Projects	9,640	0.33	0	1.08	0	25
Aid: Committed USD	9,640	112,751.20	0.00	747,564.40	0.00	18,486,564.00
Aid Sector: Administrative	9,640	0.04	0	0.22	0	2
Aid Sector: Education	9,640	0.07	0	0.30	0	5
Aid Sector: Economic Development	9,640	0.10	0	0.39	0	6
Aid Sector: Health	9,640	0.06	0	0.29	0	5
Aid Sector: Infrastructure	9,640	0.11	0	0.62	0	16
Aid Sector: Institutional Development	9,640	0.04	0	0.20	0	2
Aid Sector: Religion	9,640	0.01	0	0.08	0	2
Aid Sector: Social	9,640	0.06	0	0.27	0	3
Aid Sector: Unallocated	9,640	0.02	0	0.13	0	2
Aid Sector: Spatial Planning and Development	9,640	0.01	0	0.09	0	1
Aid Partner: Private	9,640	0.02	0	0.14	0	2
Aid Partner: Government	9,640	0.04	0	0.43	0	13
Aid Partner: International private	9,640	0.01	0	0.07	0	2
Aid Partner: UN	9,640	0.03	0	0.18	0	3
Aid Partner: National NGO	9,640	0.07	0	0.34	0	6
Aid Partner: International NGO	9,640	0.16	0	0.57	0	10
Aid Partner: Bilateral	9,640	0.004	0	0.07	0	3

Table 2. Summary Statistics: District level dataset

Statistic	N	Mean	Median	St. Dev.	Min	Max
Pre-Election 2006 Dummy	840	0.38	0	0.48	0	1
GAM support (dummy)	840	0.48	0	0.50	0	1
GAM support (continuous)	840	3.75	4.12	1.98	0.62	6.74
Aid: Number of New Projects	840	3.74	0	9.47	0	98
Aid: Committed USD	840	1,293,955.00	0.00	4,372,160.00	0.00	44,698,533.00

Table 3. Summary Statistics: Survey dataset

Statistic	N	Mean	Median	St. Dev.	Min	Max
Did the village receive tsunami aid in 2006?	756	0.07	0	0.25	0	1
Did the village receive tsunami aid in 2005?	756	0.34	0	0.47	0	1
Majority in village supported GAM	728	0.16	0	0.37	0	1
KPA active in village? (Q60)	756	0.06	0	0.25	0	1
Tsunami affected	753	0.98	0	1.80	0	19
Village Pop. (log) (Q29)	752	6.31	6.26	0.78	3.76	9.10
Percent Ethnic Acehnese (log) (Q32)	712	3.82	4.57	1.48	0.00	4.61
Number of Poor Households (Q48)	754	108.52	80	109.22	3	1,250
Primary Schools (Q53)	753	0.55	0	0.81	0	8
Number of Village Heads	756	1.02	1	0.14	1	2
Conflict Victims (Q110)	756	0.53	1	0.50	0	1
Was KPA present during Interview?	756	0.01	0	0.10	0	1
Interviewer Language - Acehnese	756	0.51	1	0.50	0	1
Interviewer Language - Other	756	0.01	0	0.07	0	1

C Data

C.1 The Recovery Aceh-Nias Database

We created the sub-district level BRR database in the following steps:

1. We accessed the online access site of the RAN database at <http://rand.bappenas.go.id/RAND/>. Since the site was last updated shortly after the shutdown of the BRR in 2009, modern web browsers did not allow the user to access customized reports from the site. We therefore used the Internet Explorer's developer tools to emulate IE v8, which was current at the time. In this way, we were able to export an overview of all aid projects in the database in an HTML table.
2. Each row in this table represents one project, including starting date, project volume, and, crucially, project locations. In each row, project locations (sub-districts) are stored in full text, without any geographic ID, separated by semicolons. We imported this HTML table into Excel.
3. We subsequently extracted the list of unique sub-district names from this file. We then tasked a research assistant to manually match all sub-districts name strings to official Indonesian sub-district IDs.
4. Combining this precise geographic information with the start date information stored in each project allowed us to merge the RAN project data into a sub-district-month panel data set based on the official sub-district IDs.

C.2 The SNPK

The SNPK is a media-based conflict event data collection initially started by the World Bank and now managed by the Coordinating Ministry for Human Development and Cultural Affairs of Indonesia ([Government of Indonesia 2018](#)).

In contrast to other, cross-national media-based conflict event datasets the SNPK has a number of advantages that make it attractive to study patterns of violence and territorial control in Aceh. First, it is based on a variety of national newspapers. Using national newspapers as data source increases the validity and coverage than using only international news sources and allows coders to pick up much more fine-grained patterns of violence. Second, the SNPK captures non-lethal forms of violence, such as kidnappings, injuries, recruitment drives, or protests—forms that get lost in many cross-national media-based conflict datasets.

For each event, the SNPK stores the sub-district ID in which the event took place. We use this information to generate our sub-district-level measure of GAM wartime support that we can match to the sub-district-month panel data set.

Like many other media-based conflict datasets, the SNPK potentially suffers from reporting bias ([Weidmann 2014](#)). To address this problem, we employ three strategies: (1) We complement our analysis with the village survey data. This helps us to capture the same phenomenon with an independently collected dataset. (2) We perform our main analyses on different levels of aggregation (sub-district and district level) to mitigate problems generated by inaccurate geolocation. (3) We perform a face validity check of the SNPK measure through data from the village level survey. (4) We replicate the analysis using the UCDP GED as an alternative data source (see [Table 7](#)).

C.3 Survey Variables

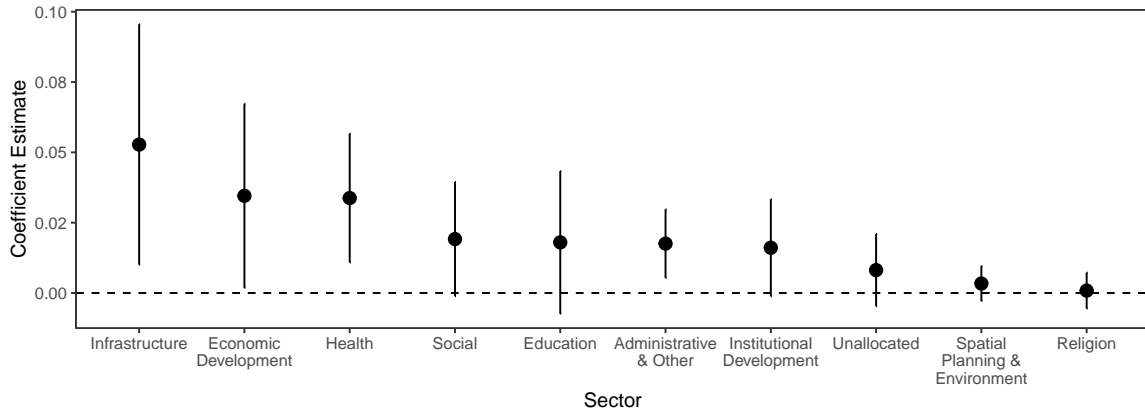
Variable	Question (Wording)	Question (Number)	Answers	Notes	Name in dataset
Did the village receive tsunami aid in 2006?	“I am now going to ask about village assistance programs. Is there Post-tsunami assistance (any kind) in this village?”	Q139	Yes / No	Question provides starting year; we code the variable for starting date in 2005 and in 2006	election_tsunami_05 election_tsunami_06
Majority in village supported GAM	“In your judgement, during this period [2001-2005], do you think the majority (at least half) of the members of the village...”	Q136	...supported GAM; ...supported TNI; ...supported neither.	We dummy code the answer “...supported GAM” with the value “1”	gam_support
Tsunami affectedness	“Were you affected in any way by the December 2004 tsunami/earthquake, or floods in the past 2 years?”	Q53 (refers to question numbering in the household survey)	“The 2004 Tsunami / earthquake: 0 1”	Information for this variable comes from a separate household survey within the villages of the village head survey. We dummy code this variable with “1” for a village to indicate tsunami affectedness of the village if at least one household in the village answered “yes” to the question.	tsunami_affected
KPA activity in village	“Are any of the following types of associations active in your village now?”	Q60	“...KPA”	“Yes” is coded as “1”	H060i_grp_kpa
Village population	“What is the total population of this village?”	Q27	Number of population	Variable is log-transformed	H027_vill_pop
Percent ethnic Acehnese	“Out of all the people in this village, approximately what proportion belongs to this ethnic group?”	Q32	Percentage	Variable is log-transformed	H032a_perc_aceh
Conflict-affected IDPs	“Are there any conflict-affected IDPs from other villages who came to this village and are here still?”	Q36	Yes/No	Dummy variable, 1 = “Yes”	H036_idp

Poverty	“ In your estimation, how many households in the village are classified as poor?”	Q48	Number of households (integer)	-	H048_poorHH
Number of primary schools	“How many completed [primary schools] were there in this village in 1998?”	Q53	Number of schools	-	H053a_primary98
Number of village heads	-	-	Number of village heads	Some villages have more than one village head	number_of_vh
Conflict victims	“Approximately how many people were killed or maimed during this period [2001-2005] as a result of the conflict, whether by TNI action, TNA action or by others?”	Q110	Estimate of conflict victims	Dummy variable = 1 if number of victims greater than zero	H110_conf_victims0105
Interviewer language	“Language Used for Interview”	Q147	Mostly Indonesian; Mostly Acehnese; Other (indicate)	We generate a dummy for each language	H147_lang
KPA presence during interview	“Who was present during the interview?”	Q152	...KPA	Dummy = 1 if KPA present	Hq152_r_6_KPA

D Testing additional implications

D.1 Alternative test of H2

Figure 1. Combatant Networks, Aid Sectors, and Benefit Allocation



Note: Estimates of the $GAM\ Area \times Pre\text{-}Election\ 2006$ coefficient from Model 1 in Panel A of Table 1 in the main paper, with 95% confidence intervals. X-axis labels indicate the respective aid sector by which the dependent variable is aggregated.

In addition to testing H2 using the ARLS survey data, we can also trace the effect of aid distribution through former combatant networks in the BRR data. In post-war and post-tsunami Aceh, former GAM combatants quickly took over jobs in the construction sector (Aspinall 2009). If former combatant networks indeed played a role in the allocation of aid, we should see particularly strong effects in those aid sectors where former combatants were most active, such as housing construction (one of the main areas of reconstruction aid). It is precisely in these sectors, where former GAM elites can most efficiently access former military networks.

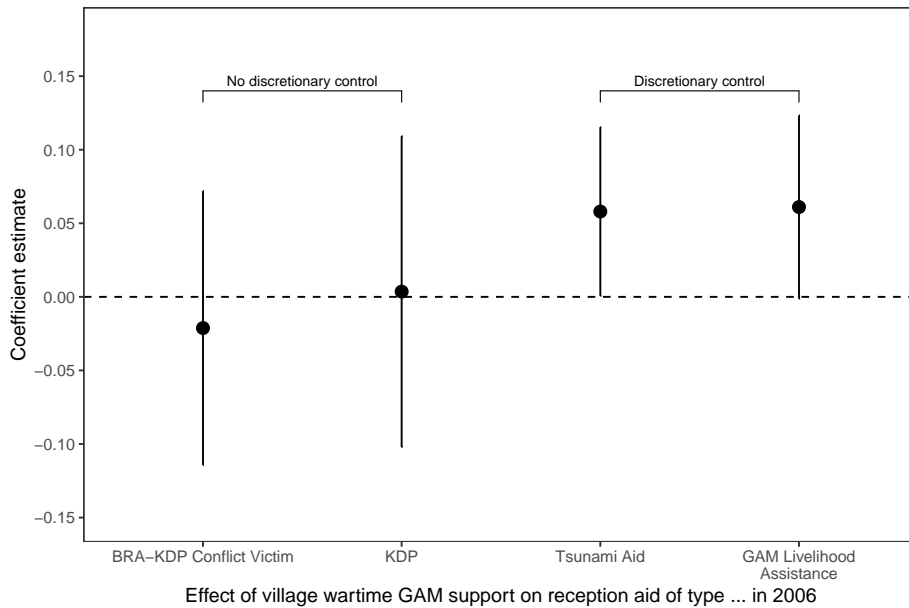
To test this proposition we replicate our main DiD specification, but aggregate the dependent variable “number of aid projects” by sector. Our empirical expectation is that pre-2006 effect in GAM support areas should be most pronounced in those sectors where former combatant networks were most active.

The results displayed in Figure 1 support this expectation. We find a particularly strong, positive, and precisely estimated effect for aid projects in the “Infrastructure” sector—the sector which subsumed the numerous housing projects coordinated by the BRR (Nicol 2013). We also find similar, but less pronounced effects in the “Economic Development” sector, which could indicate spillover effects. We interpret the results from both the survey and the BRR RAN data as evidence in support of the hypothesis that wartime military legacies play a large role in the logistics of delivering electorally motivated benefits after war.

D.2 Alternative test of H3

In addition to test H3 using the BRR data, we can also use the ARLS data to trace the effect of rebels’ discretionary control over resource on electorally targeted allocation of funds. Tsunami aid was not the only resource potentially available to rebels. The MoU also stipulated the distribution of post-conflict reintegration funds (Morel, Watanabe, and Wrobel 2009). Over the course of

Figure 2. Aid Types, Discretionary Control, and Benefit Allocation



Note: OLS/LPM results reported based on Model 6 in Panel B of Table 1 in the main paper. All models include the full set of covariates and district fixed effects. 95% confidence intervals reported, based on robust standard errors clustered on sub-district.

the implementation of the MoU, former GAM members had varying access and control over the disbursement of these reintegration funds. In February 2006, the Indonesian government established a special provincial agency, the Aceh Peace Reintegration Agency (*Badan Reintegrasi Damai Aceh*, BRA) to manage the distribution of the various conflict reparation and reintegration funds. Shortly after the establishment of the BRA in March 2006, BAPPENAS, the Indonesian development agency, allocated roughly USD 20 million of reintegration funds to the BRA. The KPA, GAM’s veteran organization, quickly captured the process of deciding where which of these funds were to go (International Crisis Group 2006a, 7).¹ For this early post-conflict “livelihood assistance,” rebel discretion over resource allocation was high. Consequently, we expect the effect of GAM wartime support on the allocation of these livelihood funds to be particularly pronounced.

Over the course of the establishment of the BRA, it quickly became clear that the agency did not have the capacity to handle the disbursement of these reintegration funds (Thorburn 2012). Consequently, the BRA cooperated with the World-Bank-funded Kecamatan Development Program (KDP), a community development program in Indonesia, to distribute reintegration funds (Morel, Watanabe, and Wrobel 2009, 2-4). Being run through the World Bank in close cooperation with the beneficiary communities, the KDP provided established mechanisms for allocation reintegration resources. Crucially, for the purposes of our hypothesis test, the BRA-KDP had strict criteria that regulated assistance delivery to sub-districts, namely conflict-affectedness and past performance in the regular KDP (see Morel, Watanabe, and Wrobel 2009, 6; Paler, Strauss-Kahn, and Kocak 2019). As a result of these criteria and their application through the World-Bank-run program, former GAM neither had any effective discretionary control over the allocation of the BRA-KDP nor over allocation of the regular KDP assistance. Consequently, we

¹The International Crisis Group (2006a, 7) describes the disbursement process as follows: “[A] group of GAM members, under a project leader who also happens to be a GAM commander, submits a proposal for a livelihood project or commercial enterprise to the [KPA]. If the KPA endorses it, the proposal goes to the BRA for funding. [...] The funds are transferred directly to the project leader (the commander), who is responsible for disbursement.”

expect a null effect of wartime GAM support on the allocation of these funds.

In addition to information about the reception of tsunami aid, the village head survey data provides data on a village's reception of the GAM Livelihood Assistance, BRA-KDP and regular KDP funds. We therefore replace the tsunami aid dummy with dummies for the reception of the other types of aid as dependent variables. [Figure 2](#) plots the coefficients, including a coefficient for the tsunami aid model for comparison.

Consistent with our expectation based on the hypothesis on discretionary control of rebels over funds, we find positive and statistically significant effects of wartime GAM support on the reception of aid only for those types of aid for which former GAM rebels had at least some discretionary control: tsunami aid ($p < 0.05$) and the GAM Livelihood Assistance ($p < 0.1$). There is also qualitative evidence that these reintegration funds were at least partially intended for electoral purposes, as [Aspinall \(2009, 13\)](#) argues: "It is also widely understood that parts of these [livelihood] funds were set aside to help cover the operational costs of GAM/KPA and of their political campaigning."

In contrast, the coefficients in [Figure 2](#) for wartime support with BRA-KDP and KDP aid as dependent variables are close to zero with wide confidence intervals, indicating insufficient information in the data to precisely determine a relationship which suggests a null effect. This suggests that for aid types where former rebels did not have discretionary control, electoral targeting did not take place, or at least not to an extent visible in the data. Moreover, the small coefficient for the BRA-KDP Conflict Victim aid projects also help to further rule out that the main effects are driven by conflict affectedness.

D.3 Internal split and organizational control

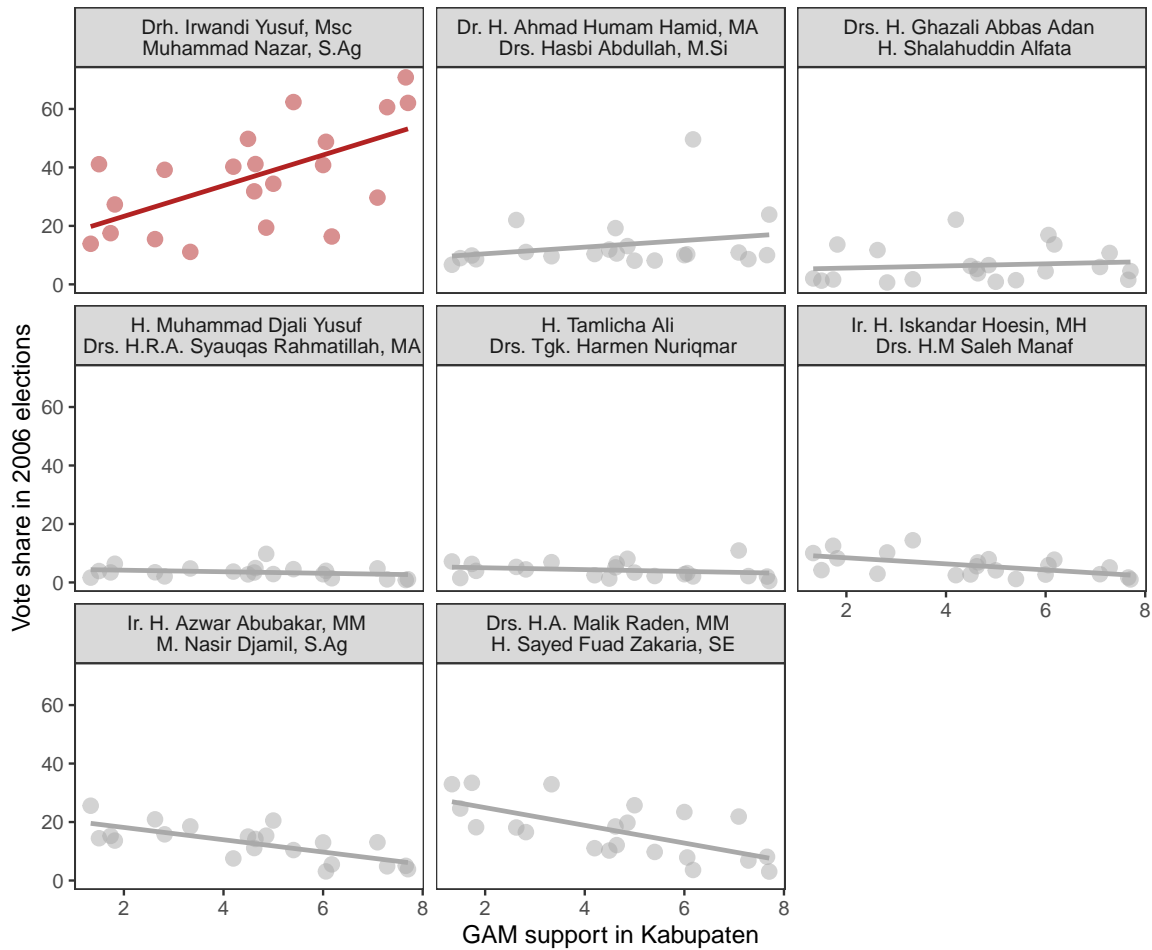
Could the split within GAM in 2006 drive the results in the paper? In the 2006 gubernatorial race, Irwandi Yusuf, a former GAM commander, and Muhammad Nazar teamed up to run for governor in Aceh.² Irwandi and Nazar competed against seven other candidates, either independent candidates or candidate teams of Indonesian national parties ([International Crisis Group 2007](#); [Stange and Patock 2010](#)). The candidacy of Irwandi Yusuf followed an internal rift among the GAM elite about whom to nominate to run for governor on behalf of the former rebel group. Irwandi Yusuf represented the candidate of the "Young Turk" faction within GAM, a group of younger GAM members. This faction opposed the candidacy of Hasbi Abdullah, candidate of the older GAM elite who largely lived abroad ([International Crisis Group 2006b](#)).

Our theoretical argument, specifically hypothesis 2, yields a clear theoretical prediction in the case of internal splits within former rebel organizations, such as the one described above: The faction that commands the strongest control over the group's former military networks should be able to use clientelism most effectively.

However, neither our subdistrict-level data nor the ARLS survey contain information on a location's factional allegiance to each of the two GAM camps that would allow us to directly test this implication. As a consequence, we test another, complementary empirical implication of the organizational control hypothesis. If the faction that controlled most of the wartime military networks is better able to effectively deploy clientelistic mobilization strategy, we should also observe that this faction ultimately performs better on election day. While this does not enable us to show directly if these factions were also better able to influence preferential resource allocation, it can serve as suggestive evidence for this proposition. To test this implication, we combine additional qualitative evidence on the level of control over the military networks in Aceh during

²Nazar was the head of the student organization SIRA.

Figure 3. District-level, wartime GAM support and 2006 vote share of all candidates in the gubernatorial elections



Note: Data points represent districts; solid lines display a regression fit between vote share and GAM support. GAM support is with the SNPK data, using the following equation: $GAM\ support_i = \frac{TNI\ BV_i + TNI\ OSV_i}{GAM\ OSV_i + 1}$ (see main text for details). Panels sorted by decreasing size of the regression coefficient. Grid labels refer to gubernatorial candidate pairs. The highlighted panel in red indicates the candidate pair with strongest links to GAM's wartime military networks.

the electoral period of 2006 with an original data collection of district-level election results for all gubernatorial candidate pairs in the 2006 election.

Two pieces of qualitative evidence suggest that Irwandi had more influence over the local GAM organizational structure in Aceh than Hasbi. First, while Hasbi had a closer relationship with the exiled GAM leadership, Irwandi had the loyalty of many of the actual GAM soldiers who fought in the years prior to 2005 (International Crisis Group 2006b, 4). These links enabled Irwandi to access the GAM military networks in a much better fashion than Hasbi. The second piece of evidence points towards the role of the KPA, the successor organization of GAM's military wing. Despite Irwandi's better connection within the military network on the ground, the old guard's senior leadership still held clout over the KPA, and thus the mobilization potential of former GAM networks in the villages. After a long period of haggling between the Hasbi and Irwandi camps, however, the leader of the KPA, Muzakir Manaf, withdrew his official support from the Hasbi ticket. This opened the enormous mobilization potential of the KPA network to Irwandi (International Crisis Group 2006b, 9).

Consequently, we expect a positive relationship between GAM support in a district and the vote share of the Irwandi ticket in this district of political candidates in post-conflict elections. Correlations between GAM support and the vote share of the gubernatorial candidates per district confirm this expectation. [Figure 3](#) plots the correlation between district-level (*Kabupaten/Kota*-level) GAM support and vote share for each candidate pair in the 2006 gubernatorial election.³ Only for the Irwandi/Nazar candidate pair (upper left panel) do we observe a positive correlation between wartime GAM penetration and vote share. The correlation is practically zero or even negative for the other candidates.

³No election results are available for sub-district/*Kecamatan*-level administrative units.

E Robustness Tests

E.1 Categorical SNPK Measure of GAM Support

We also explore the possibility that the main DiD results might be driven by our cutoff choice for the *GAM Support* variable. Figure 4 depicts cutoffs for the categorical values in the sub-district dataset used for models in Table 5. The median depicts the cutoff used for the binary variable in the main paper.

Figure 4. Distribution of continuous and categorical GAM support measure

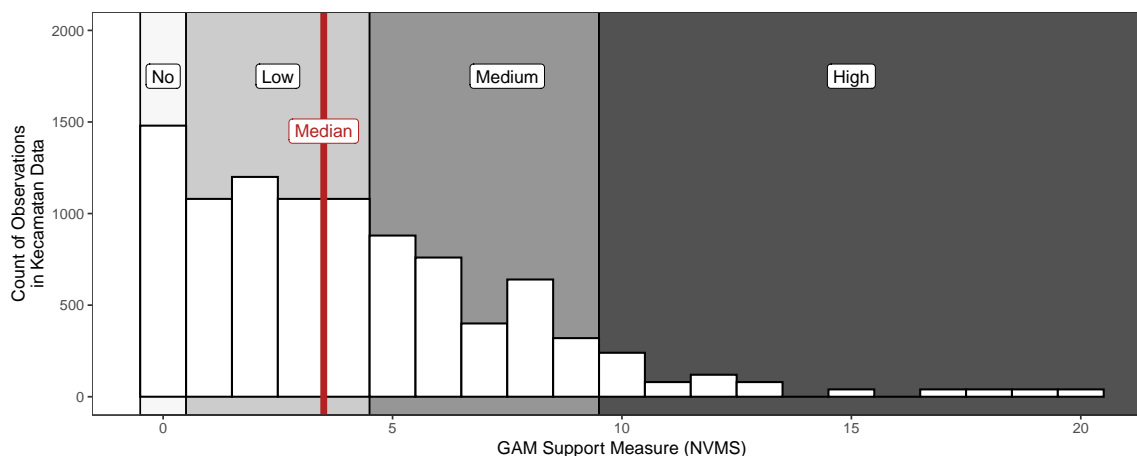


Table 5. Categorical Levels of Support: Model results

	No. of New Projects (log + 1)		Aid Volume (log + 1)	
	(1)	(2)	(3)	(4)
GAM Area (Low Support) X Pre-Election	0.13*** (0.03)	0.35 (0.44)	0.96*** (0.28)	0.95 (1.09)
GAM Area (Medium Support) X Pre-Election	0.15*** (0.03)	0.61** (0.22)	1.30*** (0.31)	2.50** (1.08)
GAM Area (High Support) X Pre-Election	0.30*** (0.09)	0.97*** (0.14)	2.22*** (0.66)	2.98*** (0.89)
Geographical Unit	Sub-District	District	Sub-District	District
Unit FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	9,640	840	9,640	840
Adjusted R ²	0.41	0.70	0.34	0.57

Note: *p<0.1; **p<0.05; ***p<0.01. Reference category for all models is “No control.”

E.2 Alternative Measures of GAM Support from the ARLS Survey

Table 6. Alternative Measures of GAM Support from the ARLS Survey

	Did village receive tsunami aid in 2006?			
	(1)	(2)	(3)	(4)
Did Gov't consider this village GAM? (Q 126)	-0.01 (0.02)			
Was a GAM base nearby this village? (Q 127)		0.02 (0.02)		
Did village voluntarily provide food for GAM? (Q 132)			0.05** (0.02)	
Did GAM soldiers sleep in the village? (Q 128)				0.04** (0.02)
Kab. FE	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Observations	685	684	701	633
Adjusted R ²	0.04	0.03	0.04	0.06

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors clustered on Kabupaten in brackets. All models include the same covariates as the models in Table 1 in the main text.

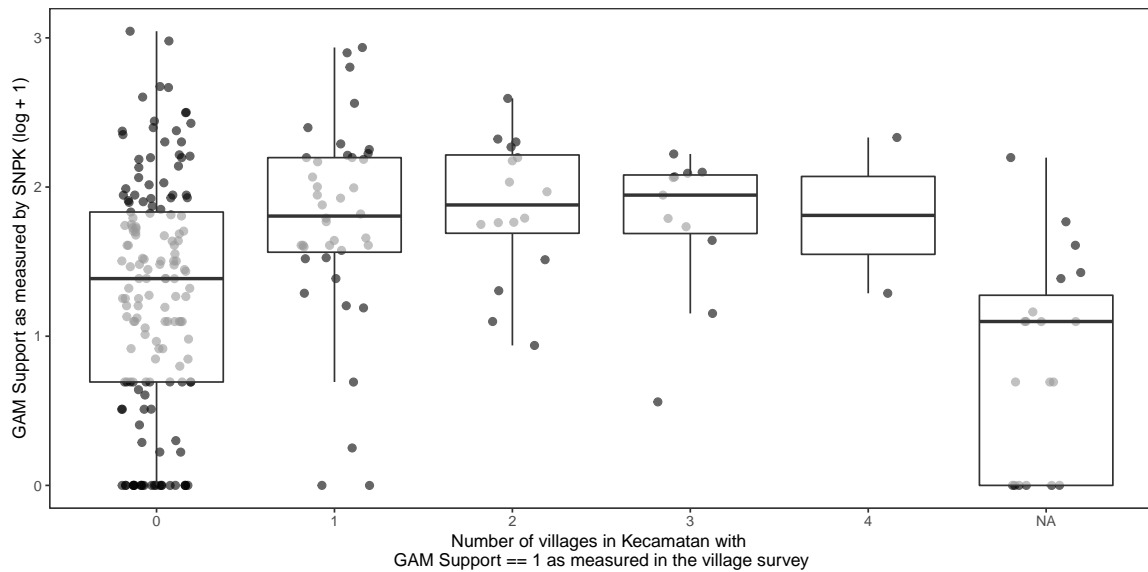
In [Table 6](#), we test the relationship between different measures of GAM support as recorded by the ARLS village head survey and the probability to receive tsunami aid in the 2006 election year. We find evidence that the relationship is driven by actual knowledge of GAM where their supporters are located instead of proxies that capture only wartime control.

The coefficient that captures government knowledge/perception of a GAM base (column 1) is negative and statistically insignificant, while the coefficient for an actual GAM base present near the village is positive, but also statistically insignificant (column 2). Both of these variables imperfectly capture territorial control or access instead of rebel support. In contrast, the coefficients for variables that represent true GAM support are positive. Positive answers to the question if the village provided voluntarily food to GAM soldiers (column 3) and if GAM soldiers did actually sleep in a village (column 4) positively and statistically significantly predict tsunami aid allocation.

These results are consistent with our expectation that GAM would allocate electorally motivated resources where they *know* that true supporters are. We interpret this as additional evidence that wartime knowledge of rebel support shapes electorally motivated benefit allocation once the violence has ended.

E.3 Data validity between ARLS and SNPK data

Figure 5. Validating SNPK GAM support measure using ARLS survey data



Note: Data points represent *Kecamatan*.

To test data validity, we aggregate the GAM support measure for each village from the ARLS to Kecamatan-level. This allows us to compare the ARLS GAM support measure to our GAM support measure computed from the SNPK. [Figure 5](#) plots the result of this exercise. The x-axis depicts the number of villages in each Kecamatan in which the ARLS survey captures a “GAM support village.” The y-axis depicts the GAM support measure (in $\log + 1$) as computed from the SNPK. We observe that as more villages are captured as GAM support villages in a Kecamatan, the higher the average GAM support measure from the SNPK. This means our SNPK measure actually picks up wartime civilian support.

E.4 UCDP Replication

Table 7. UCDP Replication

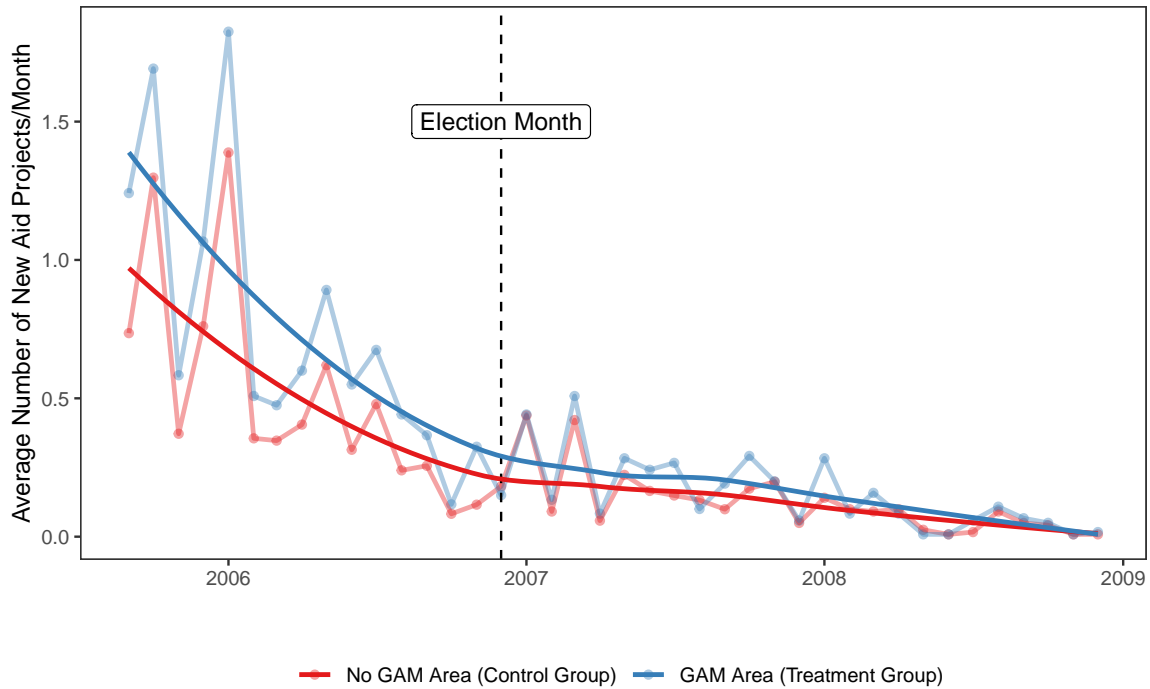
	No. of New Projects (log +1)		Aid Volume (log + 1)		Pr(New Aid Project > 0)
	(1)	(2)	(3)	(4)	(5)
GAM Area (UCDP) X Pre-Election	0.07** (0.04)	0.60** (0.22)	0.71** (0.28)	1.05 (0.89)	0.06** (0.02)
Geographical Unit	Sub-District	District	Sub-District	District	Sub-District
Unit FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	9,640	840	9,640	840	9,640
Adjusted R ²	0.40	0.70	0.34	0.56	0.34

Table 7 replicates the main BRR aid models using UCDP data on one-sided violence to construct the independent variable *GAM Support* (Pettersson and Öberg 2020). Similar to our use of the SNPK data, we spatially match UCDP GED events to sub-districts and count the number of events related to the TNI, GAM, and their respective use of one-sided violence. Subsequently, we construct the cutoff for a *GAM Support* sub-district if it lies above the median value of *GAM support* in the sample. Results in Table 7 are similar in size and statistical significance to the main models, except Model 4 that uses Committed USD as dependent variable.

E.5 Diff-in-Diff Assumptions & Robustness

The causal identification in difference in differences model relies on the assumption of parallel trends. In the Acehese context, this means we assume that, in the absence of treatment, aid trends over time are parallel in GAM and non-GAM areas (Angrist and Pischke 2009). Since in our setup the treatment occurs *before* the election in December 2006, the parallel trends assumption implies that we should see parallel trends in new aid projects *after* the December 2006 election. Figure 6 displays exactly such a trend.

Figure 6. Parallel trends plot



Note: LOESS regression lines overlaid over actual monthly means.

While the trends in Figure 6 are reassuring, we cannot rule out from Figure 6 alone that our effects are not simply picking up deviations from differential trends between treatment and control group. We therefore also estimate models that include unit-specific (i.e. sub-district or district) time trends. The parallel trends assumption of such models are considered to be less strict, since the treatment coefficient picks up deviations even from trends that are not strictly parallel (Angrist and Pischke 2015).

Another possibility is that our initial models give equal weight to units that are different in size. This could be problematic, as larger sub-districts in Aceh are typically located in mountainous regions, which are less likely to receive aid. One solution for this problem is to include unit-specific weights. We therefore estimate our difference-in-differences also with unit-specific weights (log of unit area size). A final model includes both unit-specific trends as well as unit-specific weights.

Results for all models are reported in Table 8 and remain robust, albeit somewhat smaller in substantive effect size.

Table 8. Trends and Weights

	No. of New Projects (log +1)			Aid Volume (log + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
GAM Area X Pre-Election	0.05** (0.02)	0.10*** (0.03)	0.05** (0.02)	0.59** (0.27)	1.06*** (0.26)	0.56** (0.27)
Geographical Unit	Sub-District	Sub-District	Sub-District	Sub-District	Sub-District	Sub-District
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Unit-specific Trends	Yes	No	Yes	Yes	No	Yes
Weights	No	Yes	Yes	No	Yes	Yes
Observations	9,640	9,640	9,640	9,640	9,640	9,640
Adjusted R ²	0.52	0.40	0.52	0.40	0.34	0.39

Note: *p<0.1; **p<0.05; ***p<0.01. Weights = log(Unit Size)

E.6 Spatial Correlation

Our main estimates might be biased by spatial correlation. When aid project allocation is systematically higher/lower in sub-districts whose neighbouring districts also receive aid. We address this potential problem in two ways. First, we estimate our main diff-in-diff specification with a spatial lag in the previous month. The spatial lag is the average number of aid projects in all surrounding sub-districts at $t - 1$. Second, we estimate our main models using spatially and temporally robust standard errors (Conley 2010), using software provided by Christensen and Fetzer (2015). Results are reported in Table 9 and remain robust to these alternative specifications.

Table 9. Robustness: Spatial Correlation

	No. of New Projects (log +1)				
	(1)	(2)	(3)	(4)	(5)
Spatial Lag (t-1)		0.08*** (0.01)			
GAM Area X Pre-2006 Election	0.10*** (0.03)	0.07** (0.03)	0.10*** (0.03)	0.10*** (0.03)	0.10*** (0.03)
Geographical Unit	Sub-District	Sub-District	Sub-District	Sub-District	Sub-District
Unit FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Conley SE spatial cluster	-	-	50km	100km	200km
Observations	9,640	9,399	9,640	9,640	9,640
Adjusted R ²	0.41	0.41	0.41	0.41	0.41

Note: *p<0.1; **p<0.05; ***p<0.01

E.7 Excluding West Coast from Survey Analysis

Table 10. Survey models excluding highly-affected West Coast

	Did village receive tsunami aid in 2005?				Did village receive tsunami aid in 2006?			
	OLS		Logit		OLS		Logit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Majority in village supported GAM	0.012 (0.070)	-0.027 (0.075)	0.049 (0.276)	-0.116 (0.489)	0.098** (0.045)	0.114** (0.047)	1.189*** (0.453)	1.615*** (0.557)
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
Kab. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
West Coast Excluded?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num.Obs.	455	415	421	393	455	415	399	379
R2 Adj.	0.179	0.197			0.048	0.036		
AIC			575.4	463.1			246.3	246.6

* p < 0.1, ** p < 0.05, *** p < 0.01

E.8 Survey Analysis for Tsunami Aid in 2007

Table 11. Survey results for 2007

	Did village receive tsunami aid in 2007?			
	OLS		Logit	
	(1)	(2)	(3)	(4)
Majority in village supported GAM	-0.004 (0.012)	-0.001 (0.019)	-0.229 (0.756)	-0.335 (0.979)
Covariates	No	Yes	No	Yes
Kab. FE	Yes	Yes	Yes	Yes
Num.Obs.	455	415	282	261
R2 Adj.	0.011	-0.007		
AIC			106.9	112.3

* p < 0.1, ** p < 0.05, *** p < 0.01

References

- Angrist, Joshua, and Jörn-Steffen Pischke. 2015. *Mastering 'Metrics*. Princeton: Princeton University Press.
- Angrist, Joshua David, and Jörn-Steffen Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press.
- Aspinall, Edward. 2009. "Combatants to Contractors: The Political Economy of Peace in Aceh." *Indonesia* , 1–34.
- BRR NAD-NIAS. 2009. *Story. Feat of the Daunting Launch*. Banda Aceh: BADAN REHABILITASI DAN REKONSTRUKSI NAD–NIAS.
- Christensen, Darin, and Thiemo Fetzer. 2015. "Correcting for Spatial and Temporal Auto-Correlation in Panel Data." <https://darinchristensen.com/post/conley-correction/>.
- Conley, Timothy G. 2010. "Spatial Econometrics." In *Microeconometrics*, eds. Steven N. Durlauf, and Lawrence E. Blume. Palgrave Macmillan UK , 303–313.
- Government of Indonesia. 2018. "Sistem Nasional Pemantauan Kekerasan (National Violence Monitoring System)." <https://microdata.worldbank.org/index.php/catalog/2626>.
- International Crisis Group. 2006a. *Aceh: Now for the Hard Part*. Brussels/Jakarta: International Crisis Group.
- International Crisis Group. 2006b. *Aceh's Local Elections: The Role of the Free Aceh Movement (GAM)*. Brussels/Jakarta: International Crisis Group.
- International Crisis Group. 2007. *Indonesia: How GAM Won in Aceh*. Brussels/Jakarta: International Crisis Group.
- Morel, Adrian, Makiko Watanabe, and Robert Wrobel. 2009. *Delivering Assistance to Conflict-Affected Communities : The BRA-KDP Program in Aceh*. Technical Report 53715 The World Bank.
- Nicol, Bill. 2013. *Tsunami Chronicles: Adventures in Disaster Management*. Amazon Digital Services.
- Paler, Laura, Camille Strauss-Kahn, and Korhan Kocak. 2019. "Is Bigger Always Better? How Targeting Aid Windfalls Affects Capture and Social Cohesion." *Comparative Political Studies* , 001041401985269.
- Pettersson, Therése, and Magnus Öberg. 2020. "Organized Violence, 1989–2019." *Journal of Peace Research* 57(4): 597–613.
- Stange, Gunnar, and Roman Patock. 2010. "From Rebels to Rulers and Legislators: The Political Transformation of the Free Aceh Movement (GAM) in Indonesia." *Journal of Current Southeast Asian Affairs* 29(1): 95–120.
- Thorburn, Craig. 2012. "Building Blocks and Stumbling Blocks: Peacebuilding in Aceh, 2005–2009." *Indonesia* (93): 83–122.
- Weidmann, Nils B. 2014. "On the Accuracy of Media-Based Conflict Event Data." *Journal of Conflict Resolution* 59(6): 1129–1149.